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Investor Sentiment and Stock Volatility: New Evidence from Borsa Istanbul Benchmark and Sectoral Indices[1,2]

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Abstract: This paper analyzes the effect of investor sentiment on stock returns and volatility in BIST benchmark and sectoral indices, using daily data from 2010 to 2023. Following the Baker and Wurgler methodology, we develop an Investor Sentiment Index and examine its effects on the returns and volatility of stock indices. Our findings show that investor sentiment has a significant negative effect on returns and a positive effect on the conditional volatility of Borsa Istanbul's benchmark and sectoral indices. Sub-sample analysis also emphasize that sentiment-driven investment decisions have declined in the post Covid-19 period, suggesting a shift toward more rational and information-based decision-making in the aftermath of the crisis. Finally, we assess the investment performance of BIST Sectoral Indices using portfolio performance metrics, considering the role of investor sentiment. Moreover, we classify sectors as high- or low-performing, based on how investor sentiment affects their conditional volatility to support investment decisions.

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Araştırma Makalesi *Açık Erişim*

Yatırımcı Duyarlılığı ve Pay Senedi Volatilitesi: Borsa İstanbul Gösterge ve Sektör Endekslerinden Yeni Bulgular

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Anahtar Kelimeler: Yatırımcı duyarlılığı, koşullu volatilite, portföy performansı

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Öz: bu çalışma, 2010-2023 dönemine ait günlük veriler kullanarak yatırımcı duyarlılığının Borsa İstanbul gösterge ve sektör endekslerinin getiri ve volatilitesi üzerindeki etkisini incelemektedir. Bu kapsamda Baker ve Wurgler (2006) metodolojisi takip edilerek bir Yatırımcı Duyarlılığı Endeksi oluşturulmuş ve bu endeksin pay senedi endekslerinin getirileri ve koşullu volatilitesi üzerindeki etkileri analiz edilmiştir. Elde edilen bulgular, yatırımcı duyarlılığının Borsa İstanbul gösterge ve sektör endekslerinin getirileri üzerinde anlamlı ve negatif, volatiliteleri üzerinde ise anlamlı ve pozitif etkisi olduğunu ortaya koymaktadır. Alt örneklemler ile gerçekleştirilen analizler ise Covid-19 sonrası dönemde duyarlılığa dayalı yatırım kararlarının azaldığını ve kriz sonrası dönemde daha rasyonel ve bilgi temelli karar alma eğilimine geçildiğini göstermektedir. Son olarak, yatırımcı duyarlılığının rolü dikkate alınarak portföy performans ölçütleri ile BİST Sektör Endekslerinin yatırım performansı değerlendirilmiştir. Dahası, yatırımcı duyarlılığının koşullu volatilite üzerindeki etkisine göre yüksek ve düşük performanslı sektörler sınıflandırılmış ve yatırım kararlarını desteklemeye yönelik öneriler sunulmuştur.

1. Introduction

Fama's (1970) Efficient Market Hypothesis (EMH), a cornerstone of classical finance theory, posits that asset prices always incorporate all available information, making it systematically impossible to identify over/under valued securities. EMH assumes that investors are fully rational and irrational movements in market eliminated by rational counterparts, also known as arbitrageurs. Although this hypothesis dominated the financial literature for a long time, it has increasingly been challenged with the emergence of behavioral finance approaches. As a relatively new paradigm, behavioral finance offers an alternative explanation for stock market movements by incorporating psychological factors such as emotions, biases, and moods into the financial decision-making process.

According to Kahneman and Tversky (1979), decision-making under uncertainty often deviates from rationality and is influenced by cognitive biases. This insight laid the groundwork for the emergence of behavioral finance theories and serves as the foundation for numerous later studies aimed at explaining anomalies in financial markets. In fact, a growing body of research has documented the presence of investors who engage in trading based on "rumors" or "noise" rather than on fundamental information (Black, 1986). Such noise-driven trading distorts the risk-return trade-off in capital markets and introduces additional risks beyond fundamental ones. Although mainstream finance theory states that irrational movements will be eliminated through arbitrage by rational investors, this mechanism is often limited in practice. As a result, "noise trader risk" may persist in financial markets despite the presence of arbitrageurs (De Long et al., 1990).

Many studies on behavioral finance focused on accurately measuring investors' perceptions, attitudes, or behaviors and aimed to identify investors' tendencies in financial decision-making. Moreover, studies have aimed to measure investors' optimistic or pessimistic reactions to new information arriving in the market and to assess the impact of these reactions on asset prices (Barberis et al., 1998; Shefrin, 2008). These studies have contributed to the idea that investor sentiment plays a notable role in explaining market anomalies and predicting security prices.

Investor Sentiment refers to investor expectations regarding a financial asset, which are based not on fundamental information but on noise-based information about future cash flows and asset-specific risks. (Baker & Wurgler, 2007; Barkham & Ward, 1999; Brown, 1999). Although sentiment cannot be directly observed, many widely accepted proxies are associated with investor sentiment. These proxies derived from market-based ratios or from survey measures reflecting the expectations of market participants. Recent studies have also employed indicators that capture investors' risk perceptions, as well as web-based measures such as forums and social media comments, as proxies for sentiment. In brief, there is no consensus in the existing literature on which proxies should be used to represent sentiment. Therefore, the variables selected in this study are those believed to capture sentiment in real time.

The notion that irrational behavior in capital markets may also act as a risk factor influencing return and volatility performance constitutes the main motivation of this study. Based on this motivation, the main objective of this work is to investigate whether investor sentiment has an effect on the return and volatility of the Borsa Istanbul Benchmark and Sectoral Indices. We also divided the data into sub-periods to detect the effect of investor sentiment on stock market returns and volatility across pre-Covid-19 and post-Covid-19 periods. Lastly, to assess sector-level investment performance, we conduct a performance analysis using traditional risk–reward ratios focusing on sectors that are most and least exposed to sentiment-induced volatility.

Following the Baker and Wurgler (2006) approach, we use daily data ranging from 2010-2023 to construct an investor sentiment index. For volatility modelling, we also utilize the autoregressive moving average (ARMA) and autoregressive conditional heteroscedasticity (ARCH) family models. Finally, after identifying the effect of sentiment on conditional volatility, we conduct a performance analysis using the Sharpe, Treynor, Jensen, and Sortino ratios to demonstrate the differences in investment performance between the sectoral indices that are most and least affected by sentiment-driven excess volatility. Our empirical findings indicate that investor sentiment exerts a significantly negative effect on BIST Benchmark and Sectoral Indices, while significantly and positively affecting conditional volatility. Sub-sample analyses also show that investor sentiment served as an important factor in stock markets before Covid-19, whereas its influence seems to have diminished in the post Covid-19 period. These results point out that the noisy trading activity subsided, thereby fostering more rational investment behavior. Performance analyses confirm that investment performance tends to be low to medium in sectoral indices with high sentiment-driven conditional volatility, while it is medium to high in those with low sentiment-driven volatility.

This study offers three key contributions to the existing literature. First, empirical studies using daily-frequency sentiment indicators are limited, and this study provides a novel contribution to the literature by examining how daily investor sentiment affects stock volatility. Second, we shed light on the sentiment-driven investing patterns of Turkish stock market during both crisis and non-crisis period. Lastly, we present the sectoral investment preferences considering investor sentiment and various performance metrics.

The following sections of the paper are organized as follows: Section 2 presents early and current studies on investor sentiment. Section 3 discusses the dataset of the study. Section 4 focuses on the methodology, while the findings are presented in Section 5. Section 6 concludes.

2. Related Literature

The current literature includes a wide range of research on investor sentiment. Most of these studies have investigated the link between various sentiment measures and stock market behavior. In the early phases of integrating behavioral factors into financial modeling, the focus predominantly centered on identifying market-based proxies to capture investor sentiment. Among the pioneering studies on this topic, DSSW - De Long, Shleifer, Summers and Waldmann (1990) and LST - Lee, Shleifer and Thaler (1991) models used closed-end fund discounts as a proxy for investor sentiment, providing evidence that sentiment significantly influences stock returns. Another popular study in the literature conducted by Baker and Wurgler (2006). By combining different market-based proxies, the researchers developed a sentiment index and investigated its effect on stock markets. Studies examining the effect of survey-based sentiment indicators on stock returns also emerged during the same period. In subsequent periods, many studies have incorporated investor sentiment into asset pricing models such as Capital Asset Pricing Model (CAPM), Fama-French Models (FF3FM, and FF5FM). The main motivation of these studies is to examine whether sentiment contributes to the explanatory power of these models. More recently, growing attention has been directed to web-based sentiment proxies and their influence on both stock and cryptocurrency markets. On the other hand, there are limited number of studies that aim to reveal the causal relationship between investor sentiment and stock markets, as well as the link between sentiment and stock return volatility. This section briefly reviews the existing literature on the relationship between investor sentiment and stock market behavior.

De Long et al. (1990), to the best of our knowledge, introduced the first investor sentiment model also known as the DSSW model. Their findings offer some sentiment-related empirical evidence to explain stock market anomalies such as excessive volatility, mean reversion, and closed-end fund puzzle. Similarly, Lee et al (1991) using the closed-end funds discounts (CEFD) as a proxy for investor sentiment to investigate the relationship between sentiment and stock prices. The main contribution of LST model is that the relationship between CEFD and stock returns is negative. More clearly, during the periods of prevailing pessimism, CEFD tend to widen which in turn leads to negative returns in the overall stock market. Neal and Wheatley (1998), analyzed firm-level data from 1933 to 1993 to investigate how investor sentiment influences stock returns. Results show that the CEFD and mutual fund redemptions predict the difference between small and large firm returns. Lee et al. (2002) examined the effect of sentiment on excess returns over the risk-free rate, focusing on the DJ Industrial Average, S&P 500, and the NASDAQ. Empirical findings point out that II of New Rochelle sentiment survey has a significant positive effect on returns. In another study, Brown (1999) compared survey-based and market-based sentiment measures and found a strong link between the AAII sentiment index and CEFD. On the contrary, Qiu and Welch (2006) documented that there is no relationship between consumer confidence survey and CEFD. In a more comprehensive study, Baker and Wurgler (2006), build an investor sentiment index by combining six sentiment measures (CEFD, Share Turnover, the number of IPOs, average first day returns on IPOs, equity ratio in new issues, and dividend premium) and analyzed the effect of sentiment index on stock returns. The findings indicate that during periods of high (low) sentiment, subsequent returns tend to be lower (higher) for small firms, new issues, high-volatility stocks, loss-making stocks, non-dividend-paying stocks, and extreme growth stocks.

Another group of studies in the literature has focused on consumer confidence indices as a proxy for investor sentiment, generally indicating that sentiment has a positive effect on stock markets. For instance, Kandır (2006) investigated that the effect of Turkish Consumer Confidence Index (CCI) on BIST Financial Sector returns using the monthly data from 2002 to 2005. The findings show that the CCI has a positive and significant effect on returns. Similar findings also documented by Olgaç and Temizel (2008). They investigated the long- and short-term effects of the CCI on IMKB-30 index using VAR and VECM methodologies and found a positive relationship. Contrary to previous findings, Schmeling (2009) uses cross-national data and reports a negative relationship between consumer confidence and stock market performance. Based on these results, expected returns tend to be low (high) when sentiment is high (low).

Some of the researches in the behavioral finance literature discuss the causal links between sentiment and stock prices. In studies with similar findings, Korkmaz and Çevik (2009) found a causal link between Real Sector Confidence Index and BIST-100 while Topuz (2010) reported that causality between CCI and BIST-100. Yang and Hasuike (2017) also concluded that there is a two-way causal relationship between investor sentiment and Chinese stock market. Altuntaş and Ersoy (2021) report a unidirectional causality running from BIST-100 to the CCI, as well as from the VIX to BIST-100. On the other hand, Kale and Akkaya (2016) examined the causal relationships between investor sentiment and stock returns across various sectoral indices including agriculture, financial, industrial, services, and technology, and found no evidence of causality.

Many academic papers investigate the contribution of sentiment in asset pricing models and their explanatory power. In these studies, sentiment is typically added as an additional factor to asset pricing models such as CAPM, FF3FM, and FF5FM, aiming to improve their explanatory power. For example, Changsheng and Yongfeng (2012) studied that sentiment-scaled FF3FM and its validity in Chinese stock markets. Their results emphasized that sentiment scaled model outperforms the base model in explaining stock returns. Similarly, Apergis and Rehman (2018) using the data of S&P 500 ranging from 1995 to 2015 noted that sentiment is a priced factor in stock markets. In other words, the CAPM extended with a sentiment factor provides better explanatory power for stock market returns than the baseline CAPM. Another study that investigates the effect of sentiment factor in asset pricing models conducted by Dhaoui and Bensalah (2017), who incorporate sentiment into the FF5FM. Empirical findings indicate that sentiment-scaled FF5M is more useful for predicting expected returns in NYSE. Web-based sentiment proxies also used in asset pricing studies. For instance, Ji et al. (2020) tested whether the FF3FM and its extended version with investor sentiment could explain asset returns in Chinese blockchain industry firms. They used data mining techniques to construct sentiment measures based on positive and negative comments posted on social media platform known as Guba. The results of the analysis indicate that the FF3FM model augmented with sentiment exhibits stronger predictive power. Similar evidence has been documented in the asset pricing and investor sentiment literature by Doukas and Han (2021), Yu (2021), and Muntifering (2021).

There are also studies in the current literature suggesting that investor sentiment acts as an additional risk factor in equity markets, manifesting itself in stock returns volatility. Lee et al. (2002) tested the effects of investor sentiment on U.S. stock market volatility using the Investors Intelligence (II) sentiment index and stock market data. According to the results, when volatility is high (low), investors tend to be more pessimistic (optimistic). In a similar manner, Sayim et al. (2013) found that the AAII sentiment index has a negative effect on the volatility of U.S. sectoral indices. On the contrary, Uygur and Taş (2014), utilizing trading volume as a market-based sentiment measure, reported that investor sentiment has a positive effect on the conditional variance of BIST stock returns. Aydogan (2017) analyzed the effects of sentiment on stock volatility in five different countries using TARCH model. The author utilized monthly stock market data and country-specific consumer confidence indices for the period 2004–2015. The results show that investor sentiment has a positive effect on stock volatility in Italy, Ireland, and Turkey, while it negatively affects volatility in France and Germany. Rupande et al. (2019) focuses on Johannesburg Stock Exchange in terms of the link between investor sentiment and stock volatility. The results of three different ARCH family models confirm that investor sentiment positively affects stock return volatility. Reis and Pinho (2020), Xie et al. (2023), Muguto et al. (2022), and Tseng et al. (2022) also reported comparable findings. Focusing on the cryptocurrency market, Güler (2023) analyzed the effects of investor sentiment on Bitcoin's return and volatility throughout the Covid-19 period by applying three sentiment proxies (Trading volume, Crypto Fear and Greed Index and AAII Sentiment Index) and ARCH-type models. The model findings reveal that investor sentiment positively and significantly influences Bitcoin returns and volatility, and this impact becomes more pronounced after the COVID-19 period.

This review highlights key findings from the vast literature on investor sentiment. However, as far as we know, only a limited number of studies in the current literature examine the effect of investor sentiment on stock returns volatility from the following perspectives: First, we utilize daily data with a large number of observations, in line with the recommendations in the literature for volatility analysis. Secondly, we shed some light on whether the effect of investor sentiment on stock volatility varies across different sub-periods. Furthermore, we conduct a performance analysis using traditional risk-reward ratios to highlight performance differences among sectoral indices based on their exposure to sentiment-driven volatility. Accordingly, we anticipate that this study will contribute to bridging the gap in the existing literature.

3. Data and Methodology

In this section of the study, we present our daily dataset covering the period from 2010 to 2023. In this regard, to build the investor sentiment index, we follow the Baker and Wurgler (2006) procedure by incorporating data from BIST trading volume, Turkey's 5-year CDS spreads, the CBOE Volatility Index (VIX), and the ML Option Volatility Estimate Index (MOVE) which are considered the sentiment proxies in the literature. We also utilized the BIST stock market data to analyze the effects of investor sentiment on conditional volatility. Lastly, to test the risk-return performance of stock market indices in terms of affecting sentiment-driven volatility, we use the BIST All Share Index and Turkey 3-month-bond-yield. Data for the study retrieved from the Refinitiv database. Our data used in the paper are limited to BIST and Turkey, covering the period from 2010 to 2023. Table 1 provides a summary of the dataset and variables used in the study.

Table 1. Key Variables and Descriptions

Data	Definition	Short Form
Investor Sentiment Index	BIST Trading Volume (Billion TRY)	VOL
	Turkey 5-Year Credit Default Swap Spreads	CDS
	CBOE Volatility Index	VIX
	ML Option Volatility Estimate	MOVE
BIST Benchmark Price Indices	BIST 100	XU100
	BIST 50	XU050
	BIST 30	XU030
BIST Sectoral Price Indices	BIST Banks	XBANK
	BIST Information Technology	XBLSM
	BIST Electricity	XELKT
	BIST Leasing Factoring	XFINK
	BIST Real Estate Investment Trusts	XGMYO
	BIST Food Beverage	XGIDA
	BIST Services	XUHIZ
	BIST Holding and Investment	XHOLD
	BIST Telecommunication	XILTM
	BIST Wood Paper Printing	XKAGT
	BIST Chemical Petrol Plastic	XKMYA
	BIST Financials	XUMAL
	BIST Metal Products Machinery	XMESY
	BIST Basic Metal	XMANA
	BIST Investment Trust	XYORT
	BIST Insurance	XSGRT
	BIST Industrials	XUSIN
	BIST Sports	XSPOR
	BIST Non-Metal Mineral Product	XTAST
	BIST Wholesale & Retail Trade	XTCRT
	BIST Technology	XUTEK
	BIST Textile Leather	XTEKS
	BIST Tourism	XTRZM
	BIST Transportation	XULAS
BIST Market Price Indices	BIST All Share Index	XUTUM
Risk-Free Rate	Turkey 3-month-bond-yield	TRY3MT

Source: Created by the authors.

Table 1 illustrates the proxy variables used to construct the investor sentiment index and to calculate the daily returns of BIST price indices. We used standardized values for the variables that forming sentiment index, and calculated logarithmic return series of the price indices using the following formula:

$$\boldsymbol{r_t} = ln(P_t) - ln(P_{t-1}) = ln\,(P_t/P_{t-1}) \tag{1}$$

where, r_t denotes the return of the price index in day t. P_t and P_{t-1} represents the stock price of the indices in day t and day $t-1$ respectively. In the first step, we employed Principal Component Analysis (PCA) to extract a composite investor sentiment index constructed using BIST trading volume, Turkey's 5-year CDS spreads, the CBOE VIX Index, and the MOVE Index. PCA method has been widely used in various behavioral finance studies to generate new data and has become a useful tool in constructing indices related to market sentiment. Although PCA is primarily employed for dimensionality reduction among variables, it is also utilized for data preparation in different types of analyses (Ersungur et al., 2007). In PCA, a set of p variables with interdependencies and n observations is transformed into k new variables that are linear, orthogonal, and statistically independent. The main objective of the analysis is to ensure that the k components capture as much of the original information as possible with minimal loss. Therefore, we utilized general PCA formula to construct sentiment index (Ersungur et al., 2007):

$$\boldsymbol{Y_p} = (a_p)^t\, Z = a_{1p}Z_1 + a_{2p}Z_1 + \cdots + a_{pp}Z_p \tag{2}$$

where, Z_p represents the standardized values of the data matrix, Y_p is principal component, and a_{pp} denotes component loadings that reflect the contribution of each original variable to the principal component. In common literature, it is generally suggested that variables included PCA should exhibit correlation values above 30% (Kaiser, 1974; Jolliffe, 2002; Field, 2013; Hair et al., 2019). It is particularly emphasized that correlations below this threshold may lead to low explained variance and reduce the reliability of results. In this study, variable selection for constructing sentiment index was carried out in line with this consideration. Next, we turn our attention into the volatility models to analyze the effect of sentiment on return and volatility behaviors of BIST benchmark and sectoral indices. We employ a traditional ARMA process with exogenous variable for the mean equation and EGARCH model for the variance equation to capture conditional volatility affected by sentiment. The mean equation is modeled using the following specification:

$$\boldsymbol{Y_t} = c + \sum_{i}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-q} + \theta_1\, \Delta Sent_t + \varepsilon_t \tag{3}$$

where, Y_t is the daily returns of BIST benchmark and sectoral indices, α_i reflects the influence of past returns, while β_j reflects the influence of white noise shocks. On the other hand, θ_1 denotes the effect of shift in investor sentiment. Our variance equation takes the following form:

$$\mathbf{log}(\boldsymbol{\sigma_t^2}) = \omega + \sum\nolimits_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum\nolimits_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum\nolimits_{k=1}^{r} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \theta_1 \Delta Sent_t \tag{4}$$

where, σ_t^2 is conditional variance of BIST benchmark and sectoral indices, γ_i denotes the leverage effect. α_i and β_j represents short and long term volatility (persistence) respectively. θ_1 also shows the effect of investor sentiment on conditional volatility.

Last part of the study includes performance analysis using Sharpe (1966), Treynor (1965), Jensen (1968) and Sortino (1994) ratios. All of four metrics widely used for the evaluating investment performance of various financial assets or portfolios. In this study, we utilize these metrics to compare the performance of sectors influenced by sentiment-driven volatility.

$$\boldsymbol{Sharpe} = (R_p - R_f)/\sigma_p \quad (5)$$

$$\boldsymbol{Treynor} = (R_p - R_f)/\beta_p \quad (6)$$

$$\boldsymbol{Jensen's\ Alpha} = R_p - [R_f + \beta_p(R_m - R_f)] \quad (7)$$

$$\boldsymbol{Sortino} = (R_p - MAR)/TDD \quad (8)$$

In all equations, R_p denotes the return of the asset or portfolio, R_f is the risk-free rate (Treasury bills). σ_p represents the standard deviation of portfolio while β_p is the portfolio beta. In Equation 7, R_m denotes the market return. In Equation 8 MAR and TDD represent, the minimum acceptable return and target downside deviation in the Sortino ratio, respectively. Following the aforementioned methods, the findings obtained from the dataset are presented in the next section.

4. Findings

This section gradually presents the empirical findings of the study. First, we build the sentiment index following the methodology proposed by Baker and Wurgler (2006). Second, we examine the impact of investor sentiment on BIST benchmark and sectoral indices using both the full sample and sub-sample periods. Finally, we evaluate the relationship between sentiment-induced volatility and sectoral investment performance.

4.1. Creating a Composite Sentiment Indicator

Based on Baker and Wurgler (2006), we perform a first-stage PCA using daily sentiment proxies and their lagged counterparts. Secondly, each variable contributes to the equation with the anticipated timing in capturing sentiment effects, except for the VIX. The Table 2 presents summary statistics for the proxies that to constructing sentiment index.

Table 2. Summary Statistics of Index Components

	VOL	CDS	VIX	MOVE	VOL_{t-1}	CDS_{t-1}	VIX_{t-1}	$MOVE_{t-1}$
Mean	13957019	295.9019	18.68101	73.86829	13919759	295.7951	18.67816	73.86925
Median	4561140	245.0035	16.81000	69.36	4561140.	244.9950	16.81000	69.36
Maximum	1.88E+08	906.0000	82.69000	163.7	1.88E+08	888.0300	82.69000	163.7
Minimum	542555.7	109.8180	9.140000	36.62	542555.7	109.8180	9.140000	36.62
Std. Dev.	24004207	152.5804	7.272014	22.09867	23942925	152.5427	7.271447	22.10003
Skewness	3.612043	1.416747	2.259366	1.079480	3.624058	1.418724	2.260570	1.079414
Kurtosis	18.06187	4.638858	12.93545	4.108707	18.18773	4.646217	12.94155	4.108011
Jarque-Bera	38252.74	1468.785	16331.02	806.7312	38822.31	1475.174	16350.62	806.4424
Prob.	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observation	3290	3290	3290	3290	3290	3290	3290	3290

Source: Created by the authors.

Although PCA does not require strict distributional assumptions (Jolliffe & Cadima, 2016), it can be stated that the distributions of the variables are all right-skewed, contain outliers, and do not exhibit normality. It is also essential to strike a balance between inter-factor correlations, the degree of shared variance, and the capacity to capture distinct dimensions of the dataset. Accordingly, the variables used to construct the investor sentiment index in this study were selected considering this fact. The time series and correlation matrix of the proxies are presented in Figure 1 and Figure 2 respectively.

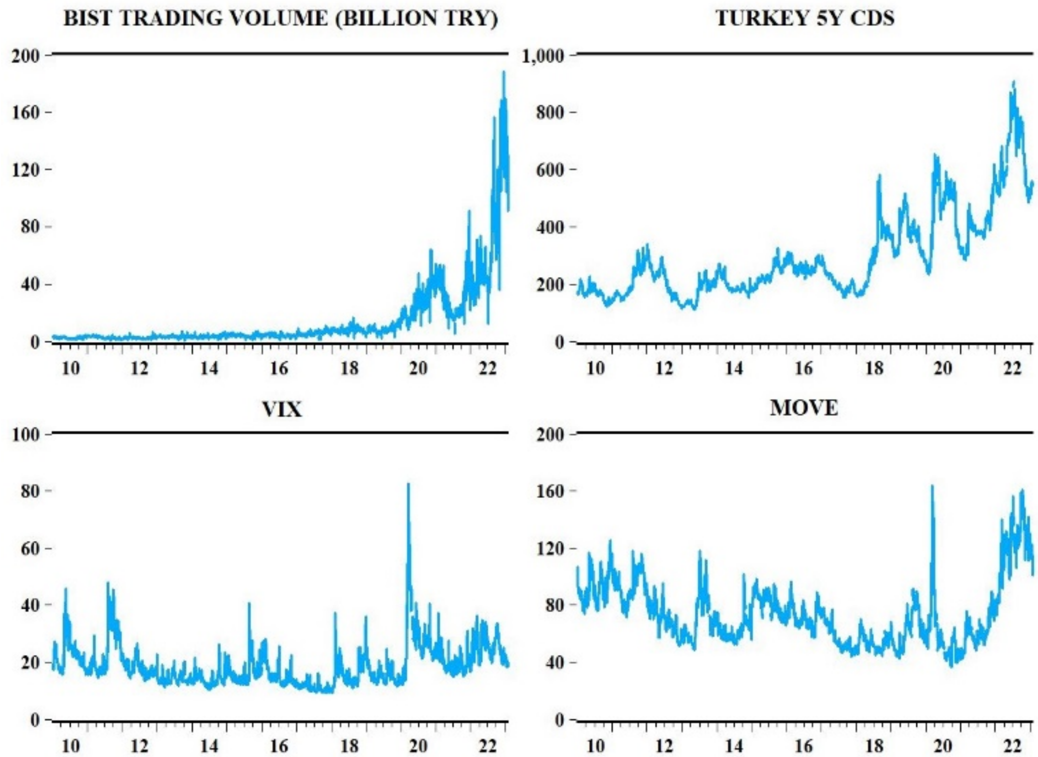

Figure 1. Time Series Plots of IS Proxies
Source: Created by the authors.

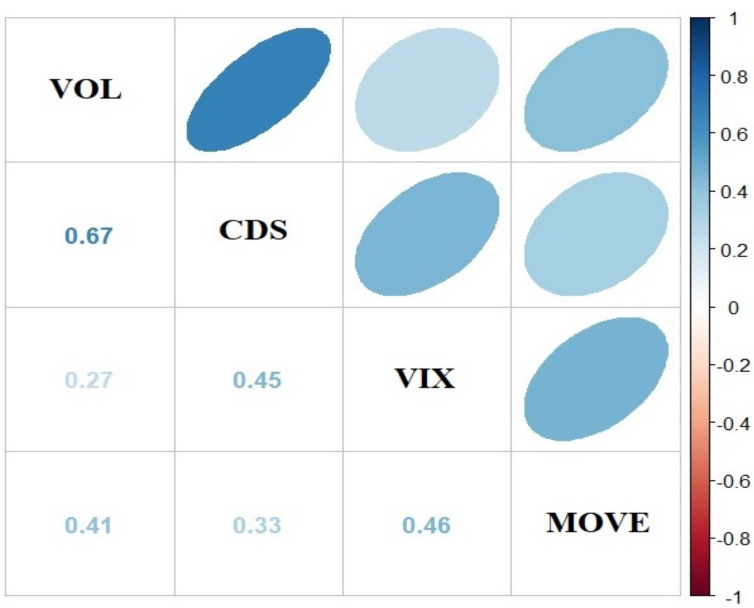

Figure 2. Correlation Matrix
Source: Created by the authors.

Figure 2 shows that all variables are positively correlated to some extent, but none exhibit extremely high or low correlation values. Therefore, it is assumed that each component and the information it carries can contribute to the principal components in a balanced manner, which, as emphasized in the literature, indicates a reliable for PCA. Accordingly, the results of the first stage PCA, conducted with standardized data for eight variables, are presented in the Table 3. Table 4 presents the contribution ratios of the first two index components to the overall index.

Table 3. First-Stage Principal Component Analysis

Component	Eigenvalue	Difference	Proportion	Cumulative Proportion
1	4.59403	2.94738	0.5743	0.5743
2	1.64665	.465719	0.2058	0.7801
3	1.18093	.670359	0.1476	0.9277
4	.510575	.477651	0.0638	0.9915
5	.0329242	.0135545	0.0041	0.9956
6	.0193697	.00607921	0.0024	0.9981
7	.0132905	.0110703	0.0017	0.9997
8	.00222013	---	0.0003	1.0000

Source: Created by the authors.

Table 4. Eigenvectors

Variable	Component 1	Component 2
BIST Trading Volume	0.3695#	-0.3685
CDS Spreads	0.3881#	-0.2811
CBOE Volatility Index	0.3233	0.4004
Option Volatility Estimate	0.3293#	0.3528
BIST Trading Volume$_{t-1}$	0.3691	-0.3687
CDS Spreads$_{t-1}$	0.3878	-0.2832
CBOE Volatility Index$_{t-1}$	0.3245#	0.4019
Option Volatility Estimate$_{t-1}$	0.3285	0.3503

Source: Created by the authors.
Note: # reflect the variables with a high absolute correlation coefficient.

Following the same procedure, we run a second-stage PCA using the four variables that exhibited the highest absolute correlation coefficients with the index. Table 5 illustrates second-stage PCA results.

Table 5. Second-Stage Principal Component Analysis

Component	Eigenvalue	Difference	Proportion	Cumulative Proportion
1	2.30849	1.47354	0.5771	0.5771
2	.834957	.238061	0.2087	0.7859
3	.596896	.337241	0.1492	0.9351
4	.259654	---	0.0649	1.0000

Source: Created by the authors.

According to these results, the proportion of sample variance explained by the first two components increased to 78.59%. Although this increase may be considered negligible, it contributes to obtaining more robust results. Table 5 also presents the contribution rates of the first two index components to the index based on the results of second-stage PCA.

Table 6. Eigenvectors

Variable	Component 1	Component 2
BIST Trading Volume	0.5212	-0.5297
CDS Spreads	0.5461	-0.3932
CBOE Volatility Index $_{t-1}$	0.4616	0.5755
Option Volatility Estimate	0.4659	0.4833

Source: Created by the authors

The following equations were derived from the contribution rates of each variable to the first and second principal components:

$$\boldsymbol{PC1} = 0.5212\boldsymbol{VOL_t} + 0.5461\boldsymbol{CDS_t} + 0.4616\boldsymbol{VIX_{t-1}} + 0.4659\boldsymbol{MOVE_t} \tag{9}$$

$$\boldsymbol{PC2} = -0.5297\boldsymbol{VOL_t} - 0.3932\boldsymbol{CDS_t} + 0.5755\boldsymbol{VIX_{t-1}} + 0.4833\boldsymbol{MOVE_t} \tag{10}$$

Building on these equations, we derive the weighted sentiment index by scaling each component series with its proportionate contribution calculated as the component's individual contribution divided by the cumulative contribution rate:

$$\boldsymbol{SENT} = PC1 * (0.5771/0.7859) + PC2 * (0.2087/0.7859) \tag{11}$$

Following this calculation, we reach the final sentiment index. The general view and change chart of the Investor Sentiment Index are depicted in Figure 3.

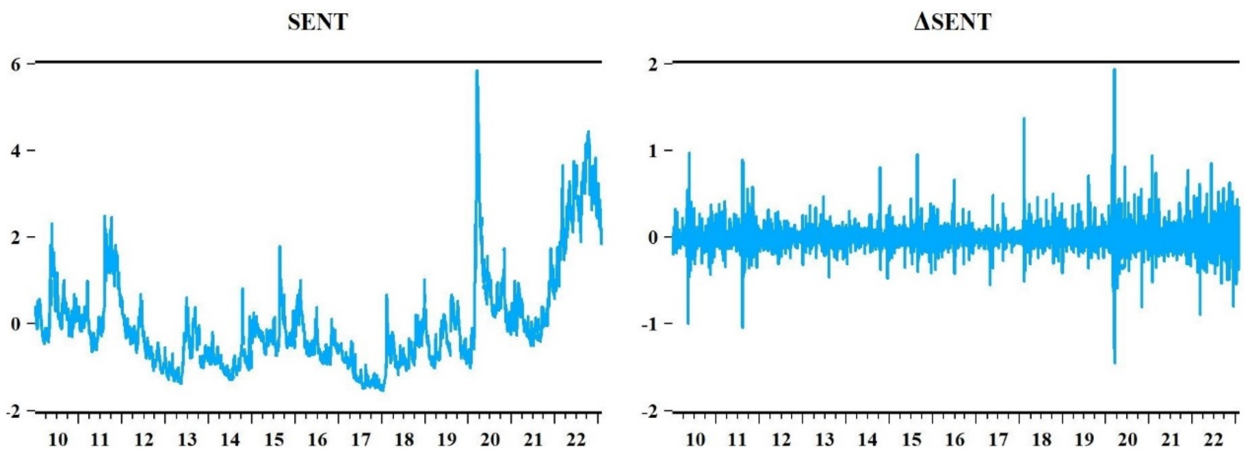

Figure 3. Time Series Graphs of Sentiment and Change in Sentiment
Source: Created by the authors

4.2. Investor Sentiment and BIST Benchmark Indices

In this section, to test our main research question, we examine the return and volatility structures of Borsa Istanbul benchmark and sectoral indices, as well as the impact of change in investor sentiment on these dynamics. First, we run a traditional ARMA and ARCH process with investor sentiment indicator to choose best-fitted ARCH family model for volatility analysis. In this manner, we perform volatility analysis for benchmark indices. Table 7 shows descriptive statistics and unit root test for BIST benchmark indices.

Table 7. Summary Statistics and Stationary Tests of BIST Benchmark Indices

	XU100	XU50	XU30	ΔSent
Mean	0.000771	0.000762	0.000759	0.000495
Median	0.001400	0.001200	0.001100	-0.009537
Maximum	0.071400	0.071900	0.075900	1.942599
Minimum	-0.104700	-0.104500	-0.103300	-1.453236
Std. Dev.	0.014966	0.015322	0.015817	0.173586
Skewness	-0.637198	-0.535932	-0.448954	1.213693
Kurtosis	7.352229	7.028748	6.661218	19.25553
Jarque-Bera	2818.396	2381.743	1947.466	37019.66
Prob.	0.000000	0.000000	0.000000	0.000000
Observation	3289	3289	3289	3289
ADF (t)	-37.9988***	-38.3619***	-38.5957***	-59.5878***
PP (t)	-57.6288***	-58.0620***	-58.2516***	-62.1702***

Source: Created by the authors.
Note: *** denotes significance of unit root tests at the 1% level.

As shown in Table 6, all return series used for volatility modeling appear to be stationary in level. XU100 has the highest daily average return throughout the data period. The return series, summarized in the table, exhibit a left-skewed distribution, while the sentiment series displays a right-skewed pattern. The results of the Jarque-Bera test indicate that none of the series follows a normal distribution. This common feature in financial time series suggests the appropriateness of applying non-parametric methods in subsequent analyses. In next step, we estimated the numerous ARMA models with exogenous sentiment factor. Considering the significance of parameters, Akaike Information Criteria (AIC), issue of overfitting, and parsimonious principles, we use most appropriate ARMAX structure for each index. We also utilized the ARCH-LM tests for detect the ARCH effects in residuals of mean model. Table 8 provides detailed information for mean models of BIST benchmark indices.

Table 8. Mean Equation Results of BIST Benchmark Indices

	ARMA Structure	Coef.	Std. Error	t-stat	Prob.	DW-stat	AIC	ARCH-LM
XU100	AR(1)	-0.847824	0.128755	-6.58479	0.0000	1.987	-5.56868	58.913 (0.00)
	MA(1)	0.826751	0.136571	6.05364	0.0000			
	ΔSENT	-0.005056	0.001501	-3.36885	0.0008			
XU50	AR(1)	-0.561958	0.204573	-2.74697	0.0060	1.981	-5.53029	56.598 (0.00)
	MA(1)	0.511813	0.212787	2.40528	0.0162			
	ΔSENT	-0.010004	0.001572	-6.36229	0.0000			
XU30	AR (1)	-0.541436	0.213302	-2.53836	0.0112	1.983	-5.46524	51.773 (0.00)
	MA(1)	0.491194	0.221296	2.21962	0.0265			
	ΔSENT	-0.009655	0.001622	-5.95088	0.0000			

Source: Created by the authors.

Table 8 provides estimation results of mean models and ARCH effect for all three benchmark indices. In line with ARCH-LM test results, we estimate both symmetric and asymmetric models to determine the best model in terms of capturing volatility dynamics for further analysis. Generally, the best information criteria were achieved at the first order for all models. Therefore, all volatility models were specified with first order terms to obtain comparable AIC results. We also extend the ARCH models with investor sentiment to show difference between AIC results. Table 9 documents the results of various volatility models.

Table 9. AIC of Symmetric and Asymmetric ARCH Models

Panel A: Univariate Model						
	GARCH (1,1)			*GJR-GARCH (1,1)*		
	Normal	Student t	GED	Normal	Student t	GED
XU100	-5.673394	-5.753212	-5.744613	-5.683281	-5.764699	-5.753281
XU50	-5.634535	-5.707609	-5.698676	-5.641910	-5.714510	-5.704236
XU30	-5.566624	-5.631337	-5.623179	-5.574616	-5.637464	-5.628379
Panel B: Sentiment Augmented Models						
XU100	-5.688812	-5.758879	-5.751894	-5.690599	-5.743328	-5.755241
XU50	-5.652818	-5.717027	-5.709054	-5.654841	-5.719815	-5.710800
XU30	-5.583007	-5.640418	-5.632842	-5.584465	-5.642717	-5.634502
Panel A: Univariate Model						
	EGARCH (1,1)			*PARCH(1,1)*		
	Normal	Student t	GED	Normal	Student t	GED
XU100	-5.646407	-5.764182	-5.755580	-5.683951	-5.744138	-5.753591
XU50	-5.642175	-5.723213	-5.705129	-5.643526	-5.714470	-5.704247
XU30	-5.571646	-5.645850	-5.631247	-5.573527	-5.637557	-5.628225
Panel B: Sentiment Augmented Models						
XU100	-5.693068#	-5.775407#	-5.756790#	-5.691485	-5.765965	-5.755530
XU50	-5.659049#	-5.730054#	-5.712042#	-5.657351	-5.720208	-5.711580
XU30	-5.588089#	-5.652985#	-5.645300#	-5.586822	-5.643206	-5.635118

Source: Created by the authors.
Note: # indicates the best information criteria among the estimation results.

As shown in Table 8, the EGARCH (1,1) model generally outperforms the other models across all three distribution types based on AIC. Therefore, the estimation results and coefficients of the EGARCH model are evaluated in this section. Table 10 presents result of EGARCH (1,1) model for all stock indices.

Table 10. Variance Equation Results of BIST Benchmark Indices

	ω	a_1	γ	β	$\Delta Sent$
XU100	-0.788743***	0.192674***	-0.090032***	0.924662***	---
	-0.625917***	0.160083***	-0.065968***	0.940850***	0.366498***
XU50	-0.736593***	0.189224***	-0.085815***	0.930002***	---
	-0.392990***	0.136232***	-0.030229***	0.965927***	0.529670***
XU30	-1.290002***	0.203767***	-0.107155***	0.865289***	---
	-0.331539***	0.124815***	-0.025382***	0.971906***	0.499704***

Source: Created by the authors.
Note: *** denotes statistical significance at the 1% level.

In Table 10, findings show that sentiment parameter has statistically significant and positive effect in terms of conditional volatility of BIST benchmark indices. Among these, the XU50 index appears to be the most influenced by investor sentiment, exhibiting the largest negative effect on returns and the strongest positive effect on volatility. Model also reveal the presence of asymmetric effects on benchmark indices. For all three indices, the asymmetry parameters are negative, indicating that volatility is higher during downturns compared to upturns. These results suggest that XU50 index is more sensitive to irrational investor behavior; the risk-return relationship for this index is more likely to be distorted by noise traders. Lastly, ARCH-LM tests also confirmed the volatility dynamics captured by EGARCH model as shown in Table 11.

Table 11. ARCH-LM test for EGARCH (1,1) model

H_0: The variance of the error terms is constant						
	XU100		XU50		XU30	
Lag Length	χ^2	Prob.	χ^2	Prob.	χ^2	Prob.
2	2.228479	0.3282	0.382297	0.8260	0.620320	0.7333
4	8.087669	0.1884	6.032916	0.1967	6.227091	0.1828
6	10.94733	0.1900	8.40796	0.2096	8.178000	0.2254
8	11.07330	0.1977	8.760897	0.3629	8.517312	0.3846
10	11.07101	0.3524	8.892948	0.5423	8.723216	0.5586

Source: Created by the authors.

4.3. Investor Sentiment and BIST Sector Indices

Having established the model underlying the analyses and identified the effect of sentiment on benchmark indices, we proceed to apply the same investigation to the sector indices. Summary statistics and unit root test results with constant & trend presented in Table 12.

Table 12. Summary Statistics and Unit Root Tests of BIST Sectoral Indices

	Mean	Median	Max	Min	Std. Dev.	Obs.	ADF (C&T)	PP (C&T)
XBANK	0.0006	0.0000	0.0994	-0.1118	0.0215	3289	-57.035***	-57.046***
XBLSM	0.0011	0.0011	0.1012	-0.1424	0.0186	3289	-50.986***	-51.070***
XELKT	0.0008	0.0010	0.0883	-0.1158	0.0175	3289	-53.643***	-53.920***
XFINK	0.0011	0.0007	0.1558	-0.1709	0.0232	3289	-51.160***	-51.211***
XGMYO	0.0007	0.0014	0.0883	-0.1114	0.0163	3289	-56.123***	-56.245***
XGIDA	0.0008	0.0011	0.0695	-0.1113	0.0153	3289	-56.497***	-56.491***
XUHIZ	0.0008	0.0012	0.0640	-0.0957	0.0133	3289	-56.211***	-56.234***
XHOLD	0.0009	0.0014	0.0729	-0.1019	0.0156	3289	-38.368***	-57.171***
XILTM	0.0006	0.0003	0.0995	-0.1029	0.0181	3289	-58.911***	-59.041***
XKAGT	0.0009	0.0013	0.0781	-0.1262	0.0171	3289	-52.352***	-52.477***
XKMYA	0.0012	0.0017	0.0791	-0.0953	0.0163	3289	-54.179***	-54.158***
XUMAL	0.0007	0.0009	0.0802	-0.1068	0.0174	3289	-57.957***	-57.961***
XMESY	0.0012	0.0017	0.0945	-0.1322	0.0162	3289	-37.761***	-56.023***
XMANA	0.0011	0.0013	0.0965	-0.1351	0.0189	3289	-58.483***	-58.472***
XYORT	0.0008	0.0007	0.1073	-0.1588	0.0157	3289	-55.453***	-55.421***
XSGRT	0.0008	0.0009	0.0836	-0.1026	0.0133	3289	-37.551***	-56.090***
XUSIN	0.0010	0.0018	0.0667	-0.1077	0.0135	3289	-37.102***	-56.143***
XSPOR	0.0007	0.0002	0.1684	-0.1883	0.0259	3289	-50.467***	-50.866***
XTAST	0.0008	0.0014	0.0659	-0.1021	0.0149	3289	-55.827***	-56.172***
XTCRT	0.0009	0.0009	0.0763	-0.0999	0.0155	3289	-56.784***	-56.913***
XUTEK	0.0013	0.0014	0.0982	-0.1406	0.0185	3289	-57.176***	-57.181***
XTEKS	0.0012	0.0017	0.0941	-0.1306	0.0165	3289	-37.306***	-55.571***
XTRZM	0.0009	0.0007	0.0941	-0.1456	0.0205	3289	-53.095***	-53.736***
XULAS	0.0014	0.0011	0.0937	-0.1407	0.0227	3289	-57.237***	-57.456***
ΔSENT	0.0005	-0.0095	1.9426	-1.4532	0.1736	3289	-59.582***	-62.170***

Source: Created by the authors.
Note: *** denotes significance of unit root tests at the 1% level.

In the Table 12, all return series used for mean and volatility models are found to be stationary at the level. More clearly, all sectoral returns series free of unit roots. Following the same criteria as in the previous analysis -ACF and PACF structures, parameter significance, AIC, and model parsimony- we estimated the mean models using the ARMA process, and the results are reported in Table 13.

Table 13. ARMAX Model Results

	AR(1)	MA(1)	AR(2)	MA(2)	ΔSENT	DW	AIC	ARCH-LM
XBANK	1.385	-1.388	-0.810	0.835	-0.008370	2.0182	-4.8497	128.3518***
XBLSM	0.416	-0.326	---	---	-0.012372	1.9970	-5.1537	250.9129***
XELKT	0.942	-0.916	---	---	-0.004084	1.9415	-5.2624	130.2091***
XFINK	0.099	---	---	---	-0.009572	2.0029	-4.7026	392.6675***
XGMYO	0.519	-0.531	---	0.054	-0.011611	1.9990	-5.4087	134.1418***
XGIDA	-0.734	0.719	---	---	-0.013323	2.0059	-5.5447	125.7819***
XUHIZ	-0.918	0.901	---	---	-0.009933	1.9865	-5.8145	73.24615***
XHOLD	---	---	---	---	-0.010161	2.0555	-5.4888	125.7453***
XILTM	-0.539	0.495	---	---	-0.009033	1.9927	-5.1875	110.7849***
XKAGT	---	0.066	---	0.043	-0.010011	1.9976	-5.3222	218.9327***
XKMYA	-0.688	0.728	0.059	---	-0.007579	1.9998	-5.4001	137.1699***
XUMAL	---	-0.039	---	0.048	-0.010660	1.9978	-5.2768	63.07619***
XMESY	-0.878	0.856	---	---	-0.011994	1.9749	-5.4239	110.9625***
XMANA	0.610	-0.629	-0.854	0.878	-0.010816	2.0454	-5.1130	44.99834***
XYORT	-1.281	1.284	-0.766	0.792	-0.008148	1.9660	-5.4747	244.8243***
XSGRT	0.914	-0.887	---	---	-0.009385	2.0438	-5.8203	107.4724***
XUSIN	-0.878	0.849	---	---	-0.011098	1.9753	-5.7851	139.7216***
XSPOR	0.604	-0.509	---	---	-0.012751	1.9797	-4.4944	372.0955***
XTAST	0.903	-0.917	0.037	---	-0.012690	1.9978	-5.5980	185.6122***
XTCRT	---	---	---	---	-0.010440	2.0215	-5.5036	81.49258***
XUTEK	0.422	-0.433	-0.930	0.920	-0.010681	2.0084	-5.1479	231.7241***
XTEKS	0.550	-0.548	---	0.066	-0.012440	1.9997	-5.3909	250.4203***
XTRZM	0.761	-0.704	---	---	-0.013993	2.0174	-4.9591	279.9146***
XULAS	0.719	-0.735	0.047	---	-0.009531	1.9975	-4.7363	140.0123***

Source: Created by the authors.
Note: *** denotes statistical significance at the 1% level.

ARCH-LM test results presented in Table 13, ARCH effects are detected in the residuals of all sector indices, showing the presence of conditional heteroscedasticity. Therefore, to enable a sectoral comparison, the volatilities of all sector indices in this stage of the analysis modelled using EGARCH (1,1) specification. In addition, two versions of the volatility model were estimated: the baseline model without sentiment and an extended model incorporating the sentiment index. Parameter estimates are presented in Table 14.

Table 14. Variance Equation of Sectoral Indices

Index	ω	a_1	γ	β_1	$\Delta Sent$	$\beta < 1$
XBANK	-0.460820***	0.181005***	-0.034353***	0.958363***	---	✓
	-0.264706***	0.121907***	-0.010758	0.977938***	0.463414***	✓
XBLSM	-1.294696***	0.416762***	-0.044275**	0.880056***	---	✓
	-1.179534***	0.393681***	-0.032384*	0.892148***	0.429294***	✓
XELKT	-0.824142***	0.260850***	-0.068721***	0.923717***	---	✓
	-0.740397***	0.241573***	-0.050011***	0.932221***	0.410525***	✓
XFINK	-0.630171***	0.330757***	-0.001273	0.950705***	---	✓
	-0.516589***	0.280286***	0.019326	0.960659***	0.572830***	✓
XGMYO	-1.067147***	0.279936***	-0.042762**	0.897749***	---	✓
	-0.918132***	0.244868***	-0.019499	0.912499***	0.598214***	✓
XGIDA	-1.626190***	0.304073***	-0.105095***	0.835814***	---	✓
	-1.186527***	0.246914***	-0.069371***	0.882657***	0.669773***	✓
XUHIZ	-3.891065***	0.348084***	-0.154758***	0.586852***	---	✓
	-0.616027***	0.168762***	-0.064906***	0.944717***	0.595596***	✓

XHOLD	-0.683144***	0.213281***	-0.060928***	0.938398***	---	✓
	-0.383252***	0.143704***	-0.026097***	0.967679***	0.512040***	✓
XILTM	-0.295188***	0.151828***	0.005264	0.977657***	---	✓
	-0.192417***	0.103177***	0.018380*	0.985923***	0.537058***	✓
XKAGT	-1.199126***	0.368050***	-0.052500***	0.889352***	---	✓
	-1.086365***	0.342152***	-0.037894**	0.900649***	0.421571***	✓
XKMYA	-0.927412***	0.250726***	-0.054030***	0.911788***	---	✓
	-0.356062***	0.140129***	-0.008858	0.970162***	0.626627***	✓
XUMAL	-0.825589***	0.194974***	-0.069860***	0.917321***	---	✓
	-0.420817***	0.129102***	-0.027861***	0.960690***	0.496774***	✓
XMESY	-0.832800***	0.271546***	-0.086346***	0.925900***	---	✓
	-0.615377***	0.225244***	-0.055777***	0.947550***	0.505089***	✓
XMANA	-0.804056***	0.224587***	-0.061792***	0.921164***	---	✓
	-0.678905***	0.195958***	-0.037090**	0.934179***	0.523821***	✓
XYORT	-0.798411***	0.317839***	0.038233**	0.934189***	---	✓
	-0.534387***	0.234188***	0.047634***	0.957925***	0.695092***	✓
XSGRT	-0.319710***	0.187561***	-0.005986	0.979729***	---	✓
	-0.208096***	0.137923***	0.011596	0.988219***	0.475210***	✓
XUSIN	-1.012304***	0.256690***	-0.132043***	0.907381***	---	✓
	-0.788622***	0.219986***	-0.095194***	0.929662***	0.617012***	✓
XSPOR	-1.069911***	0.395473***	0.037887*	0.896730***	---	✓
	-1.784864***	0.508045***	0.030359	0.816983***	0.017161	✓
XTAST	-0.783174***	0.305262***	-0.034169**	0.935973***	---	✓
	-0.620647***	0.261940***	-0.009598	0.951056***	0.592778***	✓
XTCRT	-0.802472***	0.207066***	-0.045120***	0.923176***	---	✓
	-0.567271***	0.161379	-0.027932**	0.947174***	0.549632***	✓
XUTEK	-1.040443***	0.362072***	-0.053926***	0.905512***	---	✓
	-1.089653***	0.354667***	-0.048049***	0.898819***	0.554274***	✓
XTEKS	-1.320136***	0.341109***	-0.068673***	0.873643***	---	✓
	-1.100859***	0.300313***	-0.045701**	0.896260***	0.622003***	✓
XTRZM	-0.712106***	0.292304***	-0.009149	0.937944***	---	✓
	-0.595374***	0.257216***	0.004109	0.949404***	0.367939***	✓
XULAS	-0.685919***	0.219135***	-0.059443***	0.931990***	---	✓
	-0.563767***	0.191859***	-0.040417***	0.945323***	0.365036***	✓

Source: Created by the authors.
Note: ***, **, and * denotes statistical significance at the 1%, 5% and 10% level, respectively.

As presented in Table 14, investor sentiment included in the variance equation is found to be statistically significant for the volatility of all sector indices except for the Sport Index. These results provided evidence that investor sentiment has a negative effect on the returns and a positive effect on the volatility of the selected Borsa Istanbul sub-sector indices. In the common literature, such a pattern is often attributed to the presence of noise traders in the trading venue, and a similar inference can be drawn from this analysis as well. On the one hand, we can also conclude from analysis that all sector indices has negative asymmetric volatility except Leasing Industry, Communication, Insurance and Tourism. On the other hand, Investment Trusts index shows a positive and significant asymmetry parameter. This outcome may be explained by the dominance of individual investors, the speculative nature of the securities investment trusts, and increased optimism during rising periods. It can be interpreted as a reflection of the influence of short-term investors, where positive shocks generate greater volatility. Overall, the results suggest that investor sentiment has a volatility-increasing effect across all sectors. In Figure 4 we exhibit the effect of investor sentiment on sectoral volatilities (XULAS=100).

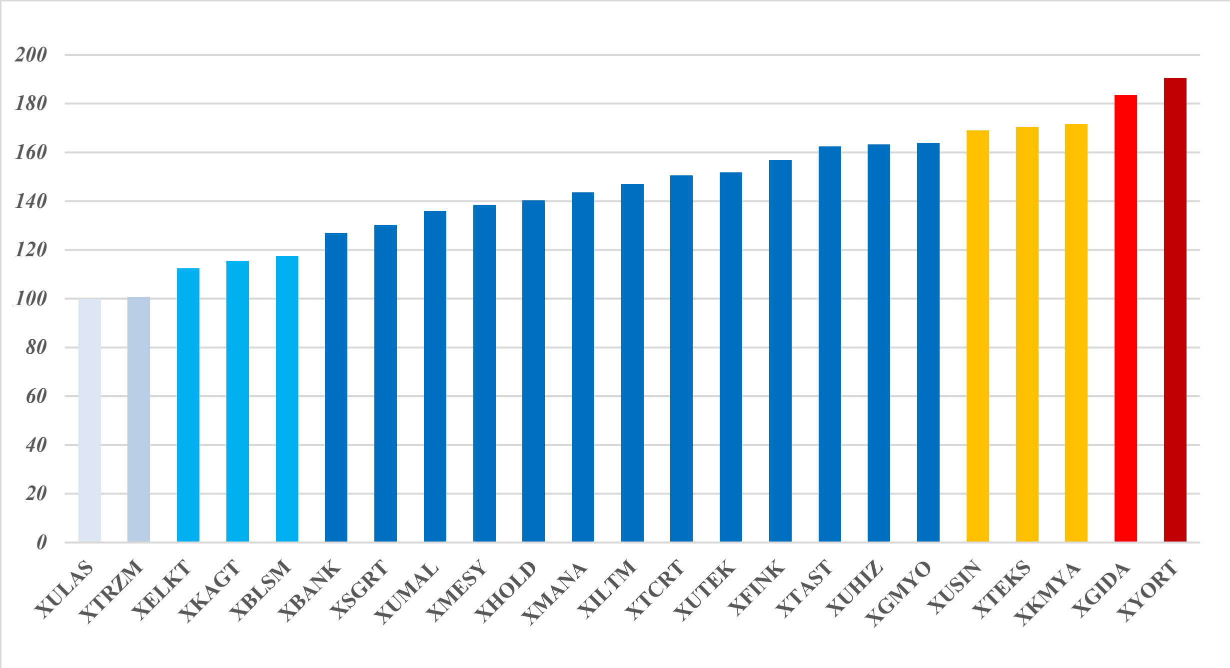

Figure 4. The Effect of Investor Sentiment on Sectoral Volatilities*
Source: Created by the authors

Figure 4 illustrates how the volatility of each sector index is affected by investor sentiment, based on the coefficient estimates of the sentiment variable obtained from the model. In this context, the Transportation Index (XULAS) volatility coefficient (0.36) is taken as the reference point (=100) for the ranking. The sectors most affected by the additional volatility generated by investor sentiment are identified as Investment Trust (XYORT), Food & Beverage (GIDA), Chemicals (XKMYA), Textile (XTEKS), and Industrial Index (XUSIN). On the other hand, the indices least affected by sentiment in terms of volatility are Transportation (XULAS), Tourism (XTRZM), Electricity (XELKT), Wood Paper Printing (XKAGT), and Information Technology Index (XBLSM). As securities investment trusts are equity-indexed and attract significant interest from individual investors, they exhibit the highest level of responsiveness to market sentiment in terms of volatility. Although the food sector is typically considered defensive by investors, it emerges as one of the indices most affected by negative sentiment. Increases in investor sentiment lead to relatively higher volatility, suggesting a stronger presence of sentiment-driven irrational decisions in this sector. Another key finding is that the Chemicals (XKMYA), Textile (XTEKS) and Industrial (XUSIN) Indices are more affected by sentiment-driven volatility. Due to their reliance on raw materials and energy costs, these sectors are particularly sensitive to global commodity price fluctuations, making them more exposed to uncertainty during period of heightened investor sentiment and speculative behavior. Sectors moderately affected by sentiment in terms of volatility include indices with a high share of intuitional investors (e.g., banking, insurance, and finance), those involving holding and investment companies, and indices

* BIST Sports Index is excluded due to statistically insignificant.

representing industrial, consumer, and service firms. Given the stabilizing role of institutional investors and the volatility-amplifying behavior of retail investors, this moderate volatility response appears to be an expected and reasonable outcome. Transportation (XULAS), Tourism (XTRZM), Electricity (XELKT), Wood-Paper Printing (XKAGT), and Information Technology (XBLSM) are the sector indices least affected by sentiment-driven volatility. Especially electricity, Wood-Paper, and IT are typically defensive sectors with stable demand and lower sensitivity to economic cycles, making them less responsive to short-term shifts in sentiment.

Overall, the findings indicate that investor sentiment negatively affects returns and positively affects conditional volatility across BIST Sectoral Indices. In other words, rising sentiment reduces average returns while increasing return volatility. This highlights the effect of irrational behavior or noise traders on the risk-return relationship, helping to identify how sensitive each sector is to sentiment. Therefore, investors planning to allocate capital to these sectors would benefit from incorporating sentiment factor in to their decision-making processes, as it plays a critical role in shaping return and volatility dynamics.

4.4. Investor Sentiment Shifts in the COVID-19 Era

In the study, we also shed light on the effect of sentiment on stock market volatility before and after Covid-19 period. March 11, 2020 –the date when the WHO (World Health Organization) declared a global pandemic- is used as a reference point to assess whether market dynamics have shifted. Accordingly, separate analyses were conducted for the relatively stable period from 2010 to 2020 and for the post-pandemic period. The findings are then employed to investigate whether investor sentiment significantly influences stock market returns and volatility across these distinct periods. EGARCH Model results for all benchmark and sectoral index presented in Table 15.

Table 15. Volatility Dynamics of BIST Benchmark and Sectoral Indices Pre and Post Covid-19 Period

Index	Pre Covid-19 (2010-2020)					Post Covid-19 (2020-2023)				
	Sentiment & Return	Sentiment & Volatility	Asymmetric Volatility	Short Term Volatility	Long Term Volatility	Sentiment & Return	Sentiment & Volatility	Asymmetric Volatility	Short Term Volatility	Long Term Volatility
XU100	-	+	-	0.100760***	0.942211***	-*	#	-	0.252710***	0.834318***
XU50	-	+	-	0.091983***	0.957632***	#	#	-	0.248044***	0.851165***
XU30	-	+	-	0.094299***	0.958174***	#	#	-	0.252710***	0.834318***
XBANK	-	+	-	0.060633***	0.980746***	#	#	#	0.171013***	0.971677***
XBLSM	-	+	-	0.387718***	0.886150***	#	#	#	0.449578***	0.813249***
XELKT	-	+	-	0.214219***	0.926182***	#	#	#	0.490554***	0.745386***
XFINK	-	+	#	0.312932***	0.940897***	#	#	#	0.316540***	0.931798***
XGMYO	-	+	-	0.216436***	0.909077***	-	#	#	0.361287***	0.808230***
XGIDA	-	+	-	0.190848***	0.911114***	#	#	-	0.467543***	0.697562***
XUHIZ	-	+	-	0.129377***	0.937845***	#	#	-	0.298723***	0.846366***
XHOLD	-	+	-	0.216436***	0.909077***	#	#	#	0.315705***	0.784990***
XILTM	-	+	#	0.093941***	0.972956***	#	+	#	0.106405***	0.987340***
XKAGT	-	+	#	0.331946***	0.886018***	-	#	#	0.347578***	0.773770***
XKMYA	-	+	-	0.168384***	0.911783***	#	#	#	0.287885***	0.869853***
XUMAL	-	+	-	0.079965***	0.967216***	#	#	#	0.346627***	0.756667***
XMESY	-	+	-	0.153990***	0.947934***	#	#	-	0.409680***	0.752173***
XMANA	-	+	-	0.171093***	0.908288***	#	#	#	0.266585***	0.904661***
XYORT	-	+	#	0.243289***	0.926172***	#	#	#	0.566770***	0.799460***
XSGRT	-	+	#	0.138004***	0.983246***	#	#	#	0.203690***	0.947128***
XUSIN	-	+	-	0.168827***	0.902297***	#	#	-	0.322471***	0.733387***
XSPOR	-	+	-	0.443508***	0.350528***	#	#	#	0.145322***	0.966033***
XTAST	-	+	-	0.264861***	0.909261***	#	#	#	0.379958***	0.769819***
XTCRT	-	+	-	0.122081***	0.942596***	#	#	#	0.144191***	0.965030***
XUTEK	-	+	-	0.315948***	0.912934***	#	#	#	0.405217***	0.878594***
XTEKS	-	+	-	0.257864***	0.897055***	#	#	#	0.433433***	0.698213***
XTRZM	-	+	#	0.224625***	0.932836***	#	#	#	0.385483***	0.870685***
XULAS	-	+	-	0.167131***	0.934575***	#	#	#	0.297951***	0.909071***

Source: Created by the authors
Note: ***, **, and * denotes statistical significance at the 1%, 5% and 10% level, respectively. # denotes insignificant parameter.

According to the findings, as we expected, investor sentiment had a negative effect on returns and positive effect on volatility of BIST benchmark and sectoral indices during 2010-2020 period. However, this relationship disappears in the 2020-2023 (post-pandemic) period. Sentiment effect observed before pandemic aligns with the full-sample findings, while its weakening afterward may be explained by shifts in investor profiles, aggressive monetary expansion, and changing sectoral dynamics following the crisis.

In the post-pandemic period, one can argue that individual investors began to act more based on information and macroeconomic developments. More specifically, the regulations and monetary measures implemented during the Covid-19 period suppressed sentiment-driven irrational pricing. As fear and uncertainty prevailed, a “wait-and-see” attitude replaced irrational exuberance and speculative trading. In the following period, fueled by expansionary monetary policies, inflationary pressure became dominant, leading to record highs in equity markets and a wave of new IPOs aiming to benefit from these conditions. This environment reflects a market in which stock prices moved largely in response to high inflation, and irrational or flawed behaviors had little or no effect on prices, thereby limiting sentiment-induced volatility. Therefore, the observed shift in results across periods is consistent and supports the study’s another research question.

On the other hand, while asymmetric effects are observed in the majority of sectoral indices during first period, this effect persists only in the XGIDA, XUHIZ, and XILTM indices during the second period. This indicates that the leverage effect continues in these specific indices in the post-pandemic period. Additionally, short-term volatility increased in all indices except for XSPOR during the second period. As for long-term persistence, it declined across all sector indices in the second period, except for the XTCRT index, where it increased.

4.5. Sentiment-Driven Volatility and Risk-Adjusted Performance

In this section of the paper, considering the effect of investor sentiment on conditional volatility, we evaluate the risk–return performance of BIST sectoral indices using Sharpe, Treynor, Jensen’s Alpha, and Sortino ratios. To this end, the performance of the indices over the full sample period (2010-2023) is assessed in relation to investor sentiment. Particularly, investment performance of the indices that are most and least affected by sentiment in terms of volatility provides valuable insights for future research and investment decisions. We use BIST All Share (XUTUM) index as the market benchmark, while the Turkish 3-Month Treasury Bill yield serves as short-term risk-free rate in the calculation of the performance metrics. First, we calculated the performance metrics of BIST sectoral indices and we present the results in Table 16.

Table 16. Performance Scores of Sectoral Indices

Index	Sharpe	Index	Treynor	Index	Jensen	Index	Sortino
XMANA	0,056951	XELKT	0,261582	XULAS	0,001074	XTCRT	0,084189
XUTEK	0,056912	XUTEK	0,092972	XTCRT	0,000993	XULAS	0,074506
XKAGT	0,055181	XTCRT	0,087307	XUTEK	0,000934	XMESY	0,073186
XUSIN	0,054584	XKAGT	0,084662	XMANA	0,000916	XUTEK	0,070747
XTCRT	0,053771	XBLSM	0,084655	XKAGT	0,000895	XBLSM	0,068816
XULAS	0,047650	XSGRT	0,083463	XBLSM	0,000862	XUSIN	0,068148
XBLSM	0,046609	XTEKS	0,083460	XMESY	0,000843	XMANA	0,067842
XMESY	0,045034	XFINK	0,082346	XFINK	0,000766	XKAGT	0,059082
XUHIZ	0,041408	XUMAL	0,082316	XUSIN	0,000733	XTEKS	0,054636
XTEKS	0,041022	XMANA	0,082242	XYORT	0,000640	XFINK	0,054587
XHOLD	0,038744	XMESY	0,075919	XTEKS	0,000632	XUHIZ	0,052550
XSGRT	0,038697	XULAS	0,074705	XTRZM	0,000602	XSGRT	0,052076
XYORT	0,037884	XUSIN	0,074160	XHOLD	0,000599	XHOLD	0,051785

XTAST	0,033961	XYORT	0,069716	XUHIZ	0,000546	XYORT	0,051504
XFINK	0,033209	XGMYO	0,067420	XSGRT	0,000511	XGIDA	0,043563
XUMAL	0,031381	XTRZM	0,066104	XTAST	0,000501	XTAST	0,041748
XGMYO	0,030568	XUHIZ	0,064343	XELKT	0,000497	XTRZM	0,040933
XTRZM	0,029600	XTAST	0,061228	XUMAL	0,000489	XUMAL	0,038604
XELKT	0,028507	XSPOR	0,059154	XGMYO	0,000462	XGMYO	0,037056
XGIDA	0,026151	XHOLD	0,056047	XGIDA	0,000421	XELKT	0,032226
XKMYA	0,023051	XGIDA	0,049087	XKMYA	0,000393	XKMYA	0,027848
XSPOR	0,015316	XILTM	0,042740	XSPOR	0,000391	XILTM	0,021896
XBANK	0,015227	XKMYA	0,036927	XBANK	0,000318	XSPOR	0,021295
XILTM	0,015022	XBANK	0,029217	XILTM	0,000267	XBANK	0,021087

Source: Created by the authors

Second, according to the results illustrated in Table 16, we classified the top five sectoral index as "high-performing," while the bottom five were considered "low-performing." Sectors not included in either group were categorized as "moderate-performing." Table 17 shows that the performance rankings of each sector with regard to risk-reward perspective.

Table 17. Performance Rankings

Ranking	Sharpe	Treynor	Jensen	Sortino
1 (H)	Basic Metal	Electricity	Transportation	Wholesale & Retail
2 (H)	Technology	Technology	Wholesale & Retail	Transportation
3 (H)	Wood & Paper	Wholesale & Retail	Technology	Metal Products Mach.
4 (H)	Industrials	Wood & Paper	Basic Metal	Technology
5 (H)	Wholesale & Retail	Information Tech.	Wood & Paper	Information Tech.
6 (M)	Transportation	Insurance	Information Tech.	Industrials
7 (M)	Information Tech.	Textile & Leather	Metal Products Mach.	Basic Metal
8 (M)	Metal Products Mach.	Leasing & Factoring	Leasing & Factoring	Wood & Paper
9 (M)	Services	Financials	Industrials	Textile & Leather
10 (M)	Textile & Leather	Basic Metal	Investment Trusts	Leasing & Factoring
11 (M)	Holding and Inv.	Metal Products Mach.	Textile & Leather	Services
12 (M)	Insurance	Transportation	Tourism	Insurance
13 (M)	Investment Trusts	Industrials	Holding and Inv.	Holding and Inv.
14 (M)	Nonmetallic Mineral	Investment Trusts	Services	Investment Trusts
15 (M)	Leasing & Factoring	Real Estate Inv. Trusts	Insurance	Food & Beverage
16 (M)	Financials	Tourism	Nonmetallic Mineral	Nonmetallic Mineral
17 (M)	Real Estate Inv. Trusts	Services	Electricity	Tourism
18 (M)	Tourism	Nonmetallic Mineral	Financials	Financials
19 (M)	Electricity	Sports	Real Estate Inv. Trusts	Real Estate Inv. Trusts.
20 (L)	Food & Beverage	Holding and Inv.	Food & Beverage	Electricity
21 (L)	Chem. Petrol & Plastic	Food & Beverage	Chem. Petrol & Plastic	Chem. Petrol & Plastic
22 (L)	Sports	Telecommunication	Sports	Telecommunication
23 (L)	Banks	Chem. Petrol & Plastic	Banks	Sports
24 (L)	Telecommunication	Banks	Telecommunication	Banks

Source: Created by the authors

After ranking the high and low-performing indices, we further classified the sectoral indices based on the effect of investor sentiment on conditional volatility. Accordingly, the five sector indices with the least additional volatility attributed to sentiment are classified as "low," while the five with the highest additional volatility are labeled as "high." Indices that do not fall into either group are considered to be "moderately" affected by sentiment. The sector-level results, classified according to investor sentiment-induced volatility and risk-adjusted performance measures, are summarized in Table 18.

Table 18. Sector Indices by Sentiment-Induced Volatility and Performance

Index	Sentiment-Induced Volatility	Performance Metrics and Levels			
	Level	Sharpe	Treynor	Jensen	Sortino
XULAS	Low	Moderate	Moderate	High	High
XTRZM	Low	Moderate	Moderate	Moderate	Moderate
XELKT	Low	Moderate	High	Moderate	Low
XKAGT	Low	High	High	High	Moderate
XBLSM	Low	Moderate	High	Moderate	High
XBANK	Moderate	Low	Low	Low	Low
XSGRT	Moderate	Moderate	Moderate	Moderate	Moderate
XUMAL	Moderate	Moderate	Moderate	Moderate	Moderate
XMESY	Moderate	Moderate	Moderate	Moderate	High
XHOLD	Moderate	Moderate	Low	Moderate	Moderate
XMANA	Moderate	High	Moderate	High	Moderate
XILTM	Moderate	Low	Low	Low	Low
XTCRT	Moderate	High	High	High	High
XUTEK	Moderate	High	High	High	High
XFINK	Moderate	Moderate	Moderate	Moderate	Moderate
XTAST	Moderate	Moderate	Moderate	Moderate	Moderate
XUHIZ	Moderate	Moderate	Moderate	Moderate	Moderate
XGMYO	Moderate	Moderate	Moderate	Moderate	Moderate
XUSIN	High	High	Moderate	Moderate	Moderate
XTEKS	High	Moderate	Moderate	Moderate	Moderate
XKMYA	High	Low	Low	Low	Low
XGIDA	High	Low	Low	Low	Moderate
XYORT	High	Moderate	Moderate	Moderate	Moderate
XSPOR	Insignificant	Low	Moderate	Low	Low

Source: Created by the authors

Table 17 highlights that sectors with low sentiment-induced volatility tend to exhibit medium to high performance levels, whereas sectors with high sentiment-induced volatility generally show medium to low risk-adjusted returns. This result confirms that heterogeneous influence of investor sentiment across sectors and supports the argument that irrational decisions and non-information-based trading activity can negatively influence investment performance. On the other hand, despite a moderate level of sentiment-driven volatility, low performance is observed in the banking and telecommunication indices, while sectors such as basic metal, wholesale & retail, and technology demonstrate stronger investment performance. Another notable finding is that holding sector (classified as low performing) shows similar behavior across Treynor measure, while the metal products machinery (classified as high performing) exhibits consistency under Sortino ratio. These findings suggest that the irrational effects driven by sentiment are relatively limited for these sectors and performance measures, indicating that the sentiment index may not serve as a useful indicator for these sectors. Finally, Figure 5 and Figure 6 shows the positioning of sectoral indices taking into account performance metrics and the effect of investor sentiment on conditional volatility.

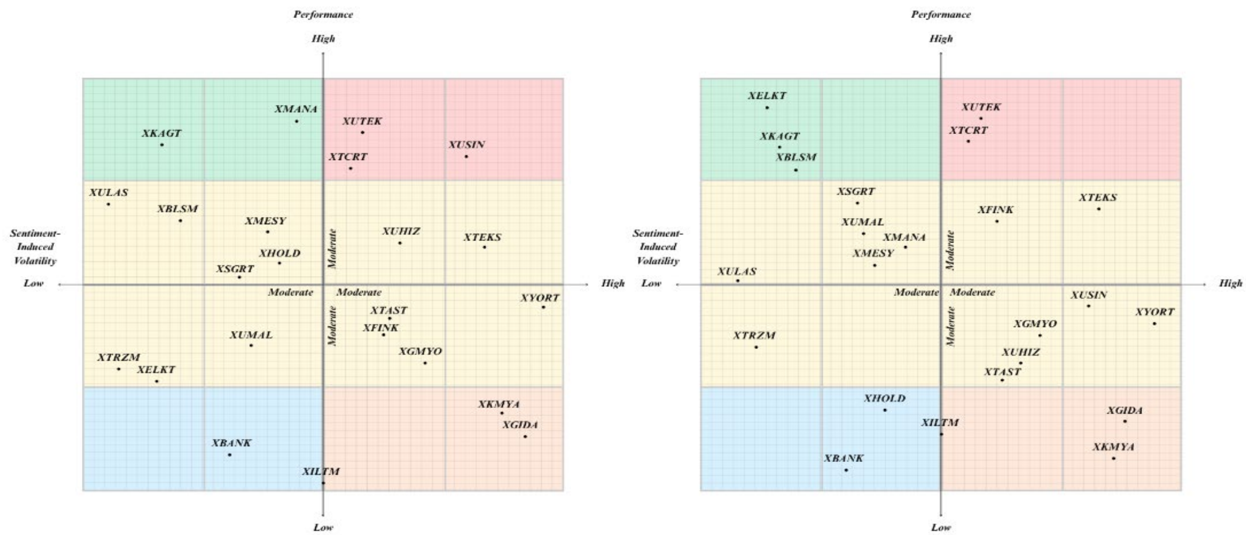

Figure 5. Sentiment-Induced Volatility and Risk-Adjusted Performance (Sharpe and Treynor)
Source: Created by the authors

In Figure 5, it can clearly be seen that Wood & Paper (XKAGT) and Basic Metal (XMANA) indices emerge as the most attractive sectoral indices for developing an investment strategy that incorporates investor sentiment and Sharpe measure. Conversely, Chemical, Petrol & Plastic (XKMYA) and Food & Beverage (XGIDA) indices are identified as low performing and more sensitive to changes in investor sentiment, and therefore may be considered less favorable options for investment decisions. Treynor measure also highlight Electricity (XELKT), Wood & Paper (XKAGT), and Information Technologies (XBLSM) as sectoral indices that are both minimally affected by sentiment-induced volatility and exhibit strong performance. Similarly, the results for Chemical, Petrol & Plastic (XKMYA) and Food & Beverage (XGIDA) align with those observed under the Sharpe measure. Figure 6 illustrates the sectoral positioning charts based on Jensen's Alpha, the Sortino ratio, taking into account the effect of investor sentiment on conditional volatility.

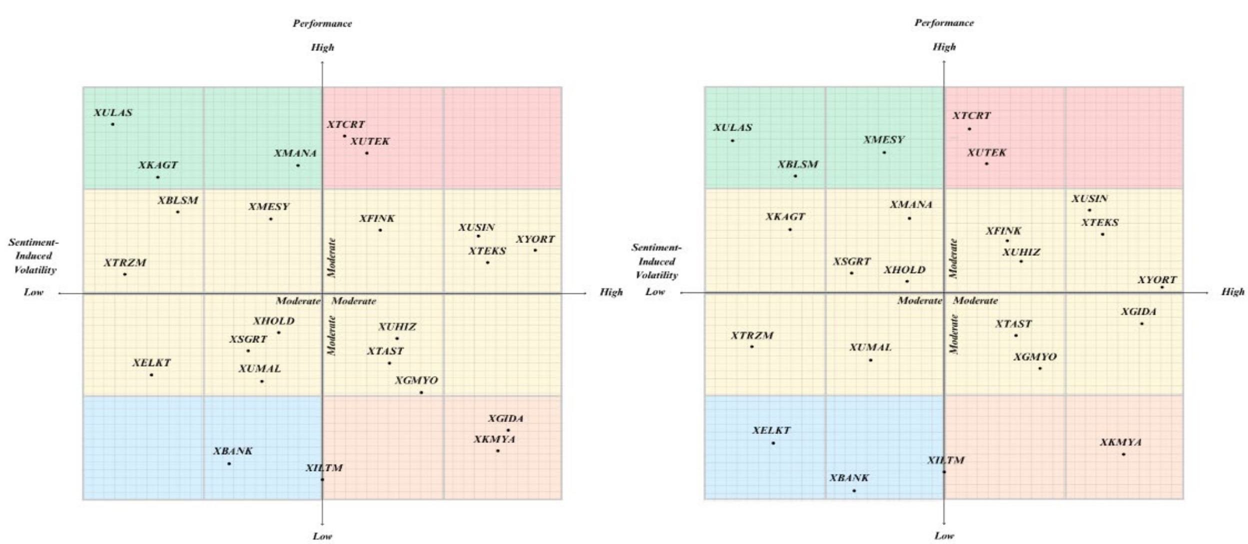

Figure 6. Sentiment-Induced Volatility and Risk-Adjusted Performance (Jensen and Sortino)
Source: Created by the authors

Regarding the Jensen ratio, results indicate that Transportation (XULAS), Wood & Paper (XKAGT), and Basic Metal (XMANA) emerge as favorable sectors for investors who consider sentiment, whereas Chemical, Petroleum & Plastic (XKMYA) and Food & Beverage (XGIDA) remain disadvantageous, consistent with previous metrics.

The Sortino measure, which accounts for downside risk, also provides valuable insights for investment decisions, revealing that Transportation (XULAS), Information Technologies (XBLSM), and Metal Products Machinery (XMESY) sectors are both resilient to sentiment-induced risks and rank among the top-performing sectors. On the other hand, only Chemical, Petroleum & Plastic (XKMYA) simultaneously exhibits poor performance and high exposure to sentiment-driven volatility.

These findings reinforce the notion that investor sentiment is a significant element in financial decision-making and should be considered in asset allocation, portfolio adjustments, and sectoral diversification strategies.

5. Discussion and Conclusion

A large body of research on Behavioral Finance focuses on measuring behavioral patterns such as perception, attitude, emotion, bias, panic, fear or appetite that deviate from fundamental financials. Today, technology has led to a diversification of financial instruments and indicators, the global integration of financial markets, and the strengthening of dynamic interconnections between markets. These developments have significantly contributed to studies aiming to modelling emotional states through market-based indicators, leading to the introduction of the concept of Investor Sentiment into financial literature.

Investor Sentiment refers to financial behavior shaped not by rational expectations or information-based decisions, but by psychological tendencies, perceptions, and emotional reactions. In particular, many indicators that cause volatility in financial markets can influence individual investment decision and, in some cases, lead to suboptimal or erroneous decision-making. In today capital markets, sentiment can manifest its effects within very short time frames, especially during sudden episodes of fear or exuberance, and such fluctuations are believed to be better captured through indicators that respond instantly to market changes. Motivated by this perspective, we investigate the effect of market based daily sentiment indicators on stock returns and volatility. Using traditional volatility modelling process, we analyzed the BIST Benchmark and Sectoral Indices from 2010 to 2023. Our main findings indicate that sentiment statistically significant negative effect on returns and significant positively on returns volatility in full-sample period, consistent with the results of Rupande et al. (2019), Muguto et al. (2022) and Tseng et al. (2022). As stated by the findings, among the benchmark indices, XU50 exhibits the highest level of sentiment-induced excess volatility, while XU100 shows the lowest. From a sectoral perspective, Investment Trust (XYORT) index experiences the greatest increase in volatility due to investor sentiment, whereas Transportation index shows a smallest increase. These findings highlight varying degrees of investor sentiment exposure across indices, shaped by market capitalization and sectoral characteristics. The sentiment index thus offer valuable insights, particularly for sector-based portfolio strategies and asset allocations.

Our sub-sample analyses also highlight the changing impact of investor sentiment on stock markets, particularly following crises such as Covid-19. In our case, we obtain similar findings for the sub-sample period (2010-2020). Nevertheless, during the post-Covid-19 period (2020-2023), the strength of this relationship diminishes considerably and is no longer evident in many sectors. The results indicate that, due to regulatory bodies implemented after the pandemic, expansionary monetary policies, and increased uncertainty, investor behavior becomes more cautious and grounded in rationally. Investor sentiment acts as a factor that increases market volatility during normal and relatively stable periods but loses its influence on price formation during global crises and their aftermath. Consequently, developing period-specific strategies that incorporate investor sentiment provides clear benefits for investors, particularly during times when regulations are relaxed or uncertainty decreases.

Finally, the performance analysis conducted for sector indices over the full sample period (2010-2023) to test the effectiveness of Investor Sentiment index generally reveals that sectors highly affected by sentiment-induced volatility exhibit moderate to low performance, whereas sectors less affected tend to show moderate to high performance. These findings provide evidence of the influence of sentiment on portfolio performance and align with empirical results consistent with the theoretical framework offered by behavioral finance.

This study's results differ across variations in sample characteristics, time horizons, frequency of data, sentiment indicators, and methodological approach. Using historical data from 2010 to 2023 on Borsa Istanbul Benchmark and Sectoral equity indices provide new evidence for the presence of behavioral effects and noise in stock markets, thereby contributing to the behavioral finance literature. Future research on investor sentiment may uncover complex relationships that traditional models struggle to capture by employing various machine-learning methods. Additionally, the effects of investor sentiment could be tested in the context of debt markets or derivative markets. Moreover, by considering the sensitivities of individual or institutional investors toward sustainable financial products, studies investigate how sentiment indicators interact with sustainable financial markets. Ultimately, every parameter that affects the performance of financial assets traded in capital markets passes through the filter of investor perception and becomes a determinant in their decision-making. Therefore, the ability of investors to accurately perceive sentiment-driven risks in the markets will enhance their investment performance.

6. Conflict of Interest Statement: The authors have no conflicts of interest to disclose.

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8. Author Contributions: M.S.: idea, design, literature review, data collection, analysis; G.S: supervision, comment, critical review. All authors have read and approved the final version of the article to be published.

9. Ethics Committee Statement: The study utilized data that do not necessitate ethics committee approval. The data used in the study were obtained from open-access sources, and the relevant data sources are specified within the text.

10. Data Availability: The data used in this study is publicly available, and the required explanations are provided within the text.

11. Use of Artificial Intelligence: In this study, limited AI tools were used solely for language editing purposes.

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